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From Measurement to Judgment: Identifying Ai-Resilient and Ai-Vulnerable Quantity Surveying Functions in Abuja, Nigeria

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ABSTRACT: The study identifies the Abuja, Nigeria, quantity surveying functions vulnerable to AI and non-vulnerable to AI based on practitioners' perceptions, to assist in guiding upskilling and role adaptation. An electronic copy of a structured questionnaire was sent to a sample of practising quantity surveyors in Abuja. A total of 155 questionnaires were distributed and 101 valid questionnaires (65% response rate) were analysed in SPSS. The effect of AI on each of the functions, rated on a 5-point Likert scale, was measured on the basis of Mean Item Score (MIS) and Standard Deviation (SD), then analysed using Principal Component Analysis (PCA) with Varimax rotation. The highest impact was for cost estimation (MIS = 4.21), measurements and quantity take-off (MIS = 4.14) and professional development (MIS = 4.12), while the lowest were client consultation and advisory services (MIS = 3.65) and design coordination and collaboration (MIS = 3.70). PCA (KMO = 0.837; Bartlett's $p < 0.001$) resulted in the identification of four underlying dimensions explaining 63.34% of variance: strategic and commercial advisory roles, quality/compliance and professional development roles, core cost and measurement roles, and risk and cost control roles. The results showed that functions most impacted by AI cluster together around computational, data-intensive functions, while functions less impacted by AI cluster together around advisory, relational and judgment-based functions. Use of AI in cost estimation, measurement, and bill of quantities preparation should be emphasised, and professional bodies and universities need to update CPD and curricula to balance AI capability with human judgment.

KEYWORDS: Artificial Intelligence, Professional Functions, Role Impact, Principal Component Analysis, Abuja

1. INTRODUCTION

The construction industry links contractors, developers, consultants, suppliers and regulatory agencies that are all part of national output and growth (Osuizugbo and Ojelabi, 2020). Cost estimation, measurement, procurement, contract administration and advisory services to clients are key roles performed by quantity surveyors in this industry.

The use of artificial intelligence (AI) tools in the construction industry is gradually making its mark in real-world scenarios as they enable computational intelligence. These tools can be used to analyse large amounts of project information, make forecasts, automate repetitive analysis and assist in decision-making, as in cost estimation, measurement and cost control (Abioye et al., 2021; Seidu et al., 2020). Specifically, AI-assisted Building Information Modelling (BIM) has been shown to improve the speed and accuracy of cost estimation and quantity take-off processes over manual methods (Babatunde et al., 2020).

However, the influence of AI differs across roles in a quantity surveying career. Some functions are more easily automated by virtue of being data- and computation-intensive; others, which are relational, judgment-based and advisory in nature, are more resistant to automation. This distinction between AI-vulnerable and AI-resilient functions is important for upskilling, curriculum design, and planning AI adoption at the firm level.

While the construction sector has shown an increasing trend towards AI adoption, limited empirical research is available on the specific areas of quantity surveying that are most and least impacted by AI, and whether these areas form coherent underlying dimensions. This study examines the perceived effect of AI on 19 quantity surveying functions among practitioners in FCT Abuja, Nigeria, ranks these functions, and uses Principal Component Analysis to reveal their dimensional structure.

2. ARTIFICIAL INTELLIGENCE AND QUANTITY SURVEYING FUNCTIONS

The 19 functions in quantity surveying explored in this study are discussed here. The functions are derived from the general technology-adoption literature, primarily the Technology Acceptance Model (Davis, 1989), Diffusion of Innovations theory (Rogers, 2003), and the Technology-Organisation-Environment framework (Oliveira et al., 2014; Faiz et al., 2024), as well as recent empirical research on the adoption of AI, BIM, cloud computing and big data in construction and quantity surveying.

Cost Estimation. AI-based BIM systems have been observed to be more precise and efficient than the conventional quantity surveying approach (Babatunde et al., 2020). Similarly, AI and machine learning software are being used more and more to support the manual process of calculating costs in quantity surveying (Seidu et al., 2020).

Measurements and Quantity Take-Off. The use of AI for measurement and take-off has arguably been the most visible change to occur in quantity surveying practice as a result of big data and machine learning (Seidu et al., 2020). Deep learning methods applied to construction data can also aid in the automatic identification and extraction of measurable elements of a building (Akinosho et al., 2020).

Professional Development. Skill development opportunities closely relate to computer self-efficacy, a construct found to have significant implications for individual outcomes when new computing technology is introduced over time (Compeau et al., 1999). Familiarity with training and technical aspects is also recognised as a significant factor in ICT acceptance in a developing-country context (Kabir et al., 2022).

Cost Budgeting. AI-enhanced, BIM-based cost tools can aid in the preparation of more effective budgets than manual methods (Babatunde et al., 2020). The use of cloud-based digital tools has also been cited in Nigeria as one of the factors responsible for improved confidence in cost-related matters in the construction industry (Oke et al., 2023).

Preparation of Bill of Quantities. One of the most significant areas of quantity surveying practice changing as a result of AI and BIM integration is the preparation of bills of quantities (Seidu et al., 2020; Babatunde et al., 2020).

Cost Control and Monitoring. Various cloud computing use cases that enable cost-monitoring functions are prevalent throughout the construction industry (Bello et al., 2021). Confidence in ongoing project cost management has also been shown to be positively associated with cloud computing use in Nigerian construction (Oke et al., 2023).

Data Management and Analytics. The use of big data has been shown to enhance the management of resource-related data and decrease inefficiencies on construction projects (Kusimo et al., 2019). Deep learning applications in construction are also reliant on, and benefit from, large project-based datasets (Akinosho et al., 2020).

Quality Assurance and Control. Research has established that implementation of new project management practices in developing-country construction is hindered when they do not align with recognised professional standards (Aghimien et al., 2018). Confidence in outcomes generated by cloud-based digital tools has also been linked to practitioners' trust in such tools (Oke et al., 2023).

Resource Management and Allocation. Big data for resource management has been found to lead to better resource allocation and to minimise material waste on construction projects (Kusimo et al., 2019). Technological resource context is also considered a key determinant in digital technology decisions within the TOE framework (Oliveira et al., 2014).

Value Engineering and Optimization. Optimisation of design and resource-use decisions in construction is identified as an emerging application area of AI (Abioye et al., 2021). The appeal of such optimisation is captured within Diffusion of Innovations theory as relative advantage, the benefit an innovation offers over the practice it replaces (Rogers, 2003).

Financial Reporting and Analysis. As with other financial and analytic applications of AI in quantity surveying practice (Seidu et al., 2020), AI-augmented BIM cost tools are equally vital in providing more precise and timely financial reporting on construction projects (Babatunde et al., 2020).

Contract Management. The need for alignment with professional and regulatory standards is recognised as a critical challenge to incorporating new practices in developing-country construction, directly applicable to contract administration (Aghimien et al., 2018). The TOE framework also acknowledges the broader institutional and regulatory environment as influencing institutional technology choices (Faiz et al., 2024).

Market Analysis and Forecasting. The visibility of a technology's benefits to early adopters in their professional market is important to its diffusion, according to Diffusion of Innovations theory (Rogers, 2003). Competitive and market pressure is also regarded as an environmental pressure shaping technology adoption decisions within the TOE framework (Oliveira et al., 2014).

Procurement Management. Institutional and regulatory barriers have been shown to affect the implementation of new procurement practices in developing-country construction (Aghimien et al., 2018). The institutional context is also incorporated into the TOE framework as part of the broader external context affecting such decisions (Faiz et al., 2024).

Dispute Resolution and Claims Management. Machine-learning models for construction project delay prediction can be directly applied to predicting and managing disputes and claims arising from delay (Egwim et al., 2021). Hybrid AI models also contribute to making claims management more proactive (Yaseen et al., 2020).

Risk Assessment and Management. To support more proactive risk forecasting, hybrid AI models have been developed for predicting the risk of construction project delay (Yaseen et al., 2020). Machine-learning ensemble models developed specifically for construction delay prediction also aid AI-assisted risk management (Egwim et al., 2021).

Design Coordination and Collaboration. Cloud computing has been recognised as an enabler of effective coordination and information-sharing with other stakeholders on construction projects (Bello et al., 2021). Diffusion of Innovations theory further asserts that the observability of collaborative benefits is a key factor in the diffusion of such tools across a profession (Rogers, 2003).

Sustainability Assessment and Green Building Analysis. Among the various applications of AI in construction, sustainability assessment has been identified as a promising area in reviews of AI in construction (Abioye et al., 2021) and in AI-based innovation in construction project delivery (Akinradewo et al., 2023).

Client Consultation and Advisory Services. Perceived usefulness, or how a technology is seen to improve outcomes that matter to its users, is a key factor in technology acceptance (Davis, 1989). Perceived usefulness has similarly been found to significantly influence professionals' acceptance of digital tools that benefit their clients and projects (Elshafey et al., 2020).

2.1 Summary of Literature

Table 1 summarises the 19 functions reviewed above and their supporting literature.

Table 1. Summary of Functions and Supporting Literature

S/N	Function	Supporting Literature
1	Cost Estimation	Babatunde et al. (2020); Seidu et al. (2020)
2	Measurements and Quantity Take-Off	Seidu et al. (2020); Akinosho et al. (2020)
3	Professional Development	Compeau et al. (1999); Kabir et al. (2022)
4	Cost Budgeting	Babatunde et al. (2020); Oke et al. (2023)
5	Preparation of Bill of Quantities	Seidu et al. (2020); Babatunde et al. (2020)
6	Cost Control and Monitoring	Bello et al. (2021); Oke et al. (2023)
7	Data Management and Analytics	Kusimo et al. (2019); Akinosho et al. (2020)
8	Quality Assurance and Control	Aghimien et al. (2018); Oke et al. (2023)
9	Resource Management and Allocation	Kusimo et al. (2019); Oliveira et al. (2014)
10	Value Engineering and Optimization	Abioye et al. (2021); Rogers (2003)
11	Financial Reporting and Analysis	Babatunde et al. (2020); Seidu et al. (2020)
12	Contract Management	Aghimien et al. (2018); Faiz et al. (2024)
13	Market Analysis and Forecasting	Rogers (2003); Oliveira et al. (2014)
14	Procurement Management	Aghimien et al. (2018); Faiz et al. (2024)
15	Dispute Resolution and Claims Management	Egwim et al. (2021); Yaseen et al. (2020)
16	Risk Assessment and Management	Yaseen et al. (2020); Egwim et al. (2021)
17	Design Coordination and Collaboration	Bello et al. (2021); Rogers (2003)
18	Sustainability Assessment and Green Building Analysis	Abioye et al. (2021); Akinradewo et al. (2023)
19	Client Consultation and Advisory Services	Davis (1989); Elshafey et al. (2020)

3. RESEARCH METHODOLOGY

3.1 Research Design

The design of the study was a quantitative, descriptive survey, suitable for this study because it was not oriented toward manipulating variables but aimed to describe the phenomenon that exists and to obtain the opinions and views of respondents (Kothari, 2004). Structured data on the perceived impact of AI on quantity surveying roles were collected via an online questionnaire to ensure that as many respondents as possible completed it and that it was easily processed.

3.2 Population, Sampling and Response Rate

The target population comprised quantity surveyors engaged by consultancy firms, contracting firms, construction organisations and government ministries in FCT Abuja in the course of infrastructure, public works and housing projects. According to membership records of the Nigerian Institute of Quantity Surveyors, the sampling frame of quantity surveyors in FCT Abuja is 907. A minimum sample size of approximately 90 was calculated using Yamane's formula for determining sample size with a 10% margin of error. To compensate for potential non-response, 155 questionnaires were distributed, of which 101 valid responses were returned and analysed, representing a response rate of 65%. This study adopted a single structured questionnaire with several sections addressing different but related research questions; the findings of the section relating to quantity surveying functions most impacted by AI are presented in this paper, with the findings of the other sections presented separately.

3.3 Data Collection

An online structured questionnaire was developed using Google Forms and sent by e-mail to quantity surveyors in Abuja. The survey comprised two sections: Part A collected basic demographic data about respondents, and Part B collected the perceived impact of AI on 19 quantity surveying functions using a Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.4 Data Analysis and Interpretation

The data were analysed using SPSS. The background characteristics of respondents were summarised using frequency and percentage. To identify the most impactful AI functions, the 19 functions were ranked using Mean Item Score (MIS) and Standard Deviation (SD). Principal Component Analysis (PCA) with Varimax rotation was carried out to assess the coherence of the underlying dimensions among the 19 functions. To determine sampling adequacy, the Kaiser-Meyer-Olkin (KMO) measure was used, and Bartlett's Test of Sphericity was used to test the appropriateness of the data for factor analysis. An eigenvalue greater than 1.0 was accepted as the criterion for retaining components, and Cronbach's alpha was used to evaluate the internal consistency of each extracted component.

3.5 Ethical Considerations

The study did not require formal ethics review board clearance, as it was a questionnaire survey in which professional adults participated voluntarily, anonymously, and with minimal risk, and no sensitive personal information was collected. Respondents gave their informed consent before completing the questionnaire.

3.6 Limitations

The study covers only FCT Abuja, and findings might differ in other areas with varying infrastructural and institutional settings. The cross-sectional design captures perceptions at a single point in time.

4. FINDINGS

4.1 Background Information of Respondents

The study revealed that all 101 respondents were quantity surveyors practising in FCT Abuja. The sample is reasonably representative in terms of organisation size, being skewed toward large and medium organisations, and in terms of professional standing, with 81.2% of the sample holding dual membership of both MNIQS and QSRBN. The level of education is good, with more than 58% holding Bachelor's degrees. AI familiarity was high, with 73.3% of respondents reporting familiarity with more than 15 tools, putting respondents in a good position to evaluate how AI impacts their functions.

4.2 Perceived Impact of AI on Quantity Surveying Functions

Table 2 shows the perceived impact of AI on the 19 quantity surveying functions, using Mean Item Score (MIS) and Standard Deviation (SD).

Table 2. Perceived Impact of AI on Quantity Surveying Functions

S/N	Function	MIS	SD	Rank
1	Cost Estimation	4.21	0.535	1
2	Measurements and Quantity Take-Off	4.14	0.530	2
3	Professional Development	4.12	0.697	3
4	Cost Budgeting	4.11	0.598	4
5	Preparation of Bill of Quantities	4.07	0.637	5
6	Cost Control and Monitoring	3.97	0.754	6
7	Data Management and Analytics	3.96	0.720	7
8	Quality Assurance and Control	3.81	0.833	8
9	Resource Management and Allocation	3.80	0.800	9
10	Value Engineering and Optimization	3.80	0.800	9
11	Financial Reporting and Analysis	3.79	0.766	11
12	Contract Management	3.75	0.830	12
13	Market Analysis and Forecasting	3.74	0.730	13
14	Procurement Management	3.73	0.835	14
15	Dispute Resolution and Claims Management	3.71	0.942	15
16	Risk Assessment and Management	3.71	0.852	15
17	Design Coordination and Collaboration	3.70	0.867	17
18	Sustainability Assessment and Green Building Analysis	3.70	0.933	17
19	Client Consultation and Advisory Services	3.65	0.984	19

The results show that cost estimation (MIS = 4.21, Rank 1), measurements and quantity take-off (MIS = 4.14, Rank 2), and professional development (MIS = 4.12, Rank 3) have the highest perceived impact. The other high-ranked functions were cost budgeting (MIS = 4.11, Rank 4) and preparation of bill of quantities (MIS = 4.07, Rank 5), indicating that the perceived impact of AI is primarily in computational and financial functions.

Client consultation and advisory services (MIS = 3.65, Rank 19), design coordination and collaboration together with sustainability assessment and green building analysis (both MIS = 3.70, Rank 17), and dispute resolution and claims management together with risk assessment and management (both MIS = 3.71, Rank 15) are the lowest-scoring functions. Mostly, these lower-ranked functions are relational and judgment-based, consistent with the description of AI-resilient functions in Section 1.

4.3 Underlying Dimensions of AI Impact on Quantity Surveying Functions

To determine whether the 19 functions cluster into coherent underlying dimensions, the responses were subjected to Principal Component Analysis (PCA) with Varimax rotation. Sampling adequacy and the suitability of the data for factor analysis were assessed.

Table 3. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy	**0.837**
Bartlett's Test of Sphericity – Approx. Chi-Square	996.51
df	171
Sig.	< 0.001

The KMO value of 0.837 indicates meritorious sampling adequacy for factor analysis (Kaiser, 1974), and Bartlett's Test of Sphericity was statistically significant ($\chi^2(171) = 996.51$, $p < 0.001$), confirming the data are suitable for PCA. Four components with eigenvalues greater than 1.0 were extracted, jointly explaining 63.34% of total variance, as shown in Table 4.

Table 4. Total Variance Explained

Component	Eigenvalue (Total)	% of Variance	Cumulative %
1	7.281	38.32	38.32
2	2.251	11.85	50.17
3	1.391	7.32	57.49
4	1.112	5.85	63.34

Table 5 presents the rotated component matrix, showing the factor loadings of the 19 functions. Only loadings above 0.40 are shown.

Table 5. Rotated Component Matrix

Function	1	2	3	4
Contract Management	0.834			
Procurement Management	0.807			
Value Engineering and Optimization	0.678			0.404
Resource Management and Allocation	0.623	0.517		
Client Consultation and Advisory Services	0.585	0.530		
Data Management and Analytics	0.530			0.486
Design Coordination and Collaboration	0.517			
Market Analysis and Forecasting	0.487			
Professional Development		0.766		
Quality Assurance and Control		0.708		
Financial Reporting and Analysis		0.651		
Dispute Resolution and Claims Management	0.490	0.631		
Sustainability Assessment and Green Building Analysis	0.469	0.622		
Measurements and Quantity Take-Off			0.814	
Cost Estimation			0.776	
Preparation of Bill of Quantities			0.759	
Cost Budgeting			0.574	
Risk Assessment and Management				0.827
Cost Control and Monitoring				0.604

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalisation. Rotation converged in 7 iterations.

5. DISCUSSION

The naming of the four extracted components followed the convention of assigning the most salient variable(s) in each component to the component name (Field, 2013).

The Strategic and Commercial Advisory Functions (Component 1) (8 items, $\alpha = 0.888$) includes contract management, procurement management, value engineering and optimization, resource management and allocation, client consultation and advisory services, data management and analytics, design coordination and collaboration, and market analysis and forecasting. This is the largest component, with 38.32% of variance and the highest internal consistency of the four components. The combination of clearly relational functions (client consultation and design coordination) and computational functions suggests that respondents perceive these functions as a single advisory and commercial aspect of practice, rather than as clearly distinct on the basis of AI vulnerability. This is in line with the literature on AI in construction, where AI application has been shifting from analytical and computational tasks toward advisory tasks (Abioye et al., 2021).

The Quality, Compliance and Professional Development Functions (Component 2) (5 items, $\alpha = 0.83$) comprises professional development, quality assurance and control, financial reporting and analysis, dispute resolution and claims management, and sustainability assessment and green building analysis, explaining 11.85% of variance. This component reflects compliance and the continuous development of skills, consistent with the relationship between alignment with professional standards and continuous skill development as factors influencing technology acceptance (Aghimien et al., 2018; Compeau et al., 1999).

The Core Cost and Measurement Functions (Component 3) (4 items, $\alpha = 0.737$) covers measurements and quantity take-off, cost estimation, preparation of bill of quantities, and cost budgeting, accounting for 7.32% of variance. Interestingly, three of the four highest individually mean-ranked functions in Table 2 (cost estimation, measurements and quantity take-off, and preparation of bill of quantities) belong to this core, traditional and computational component of quantity surveying practice, indicating that this component is statistically distinct and individually perceived as most vulnerable to AI. This aligns with findings that AI-supported BIM tools have already been shown to improve the efficiency and accuracy of cost estimating and measurement functions (Babatunde et al., 2020; Seidu et al., 2020).

The Risk and Cost Control Functions (Component 4) (2 items, $\alpha = 0.716$) explains 5.85% of variance and includes risk assessment and management and cost control and monitoring. In line with predictive modelling of delay and risk being treated as a separate application area (Yaseen et al., 2020; Egwim et al., 2021), it is the smallest component, yet represents a continuous monitoring function distinct from the one-off computation captured in Component 3.

Ranking and component analysis indicate that AI vulnerability is concentrated in specific core functions of FCT Abuja quantity surveying practice, particularly cost estimation, measurement and preparation of bill of quantities (Component 3), while other functions such as client consultation, design coordination and professional development are statistically distinct but individually perceived as comparatively less AI-vulnerable. This is consistent with the developing-economy literature, which notes that AI applications in construction are currently concentrated on operational and task-oriented applications rather than strategic or advisory ones (Akinradewo et al., 2023).

6. CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

The current study identified, ranked and analysed the 19 quantity surveying functions perceived to be affected by AI by practitioners in FCT Abuja, Nigeria, and revealed the dimensional structure of these functions using Principal Component Analysis (PCA). The most AI-vulnerable functions were cost estimation, measurements and quantity take-off, and professional development, whereas client consultation and advisory services, and design coordination and collaboration, were more AI-resistant. PCA (KMO = 0.837; Bartlett's $p < 0.001$) reduced the 19 functions to four dimensions accounting for 63.34% of variance, with the core computational functions (Component 3) showing high factor loadings and being perceived by participants as the most AI-vulnerable dimension of practice.

6.2 Recommendations

The most critical areas for AI application in quantity surveying should be the parts of the profession that have most clearly demonstrated sensitivity to computerisation, such as preparation of bill of quantities, measurement and cost estimation. Professional bodies (NIQS, QSRBN) and universities need to adapt their continuing professional development and curricula to build AI literacy in these computational skills, while ensuring that relational, advisory and judgment-based skills continue to be reinforced. Firms should also invest in reskilling programmes that equip practitioners for more strategic and advisory work rather than the manual, computational work increasingly taken over by AI.

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8. DECLARATION OF GENERATIVE AI USE

During the preparation of this manuscript, the authors used Grammarly and QuillBot, both continuously updated cloud-based writing-assistance services without discrete version numbers, to check for grammatical, spelling, and language errors. These tools were not used to generate research content, analyse data, or draft substantive text. The authors have reviewed and edited all output as needed and take full responsibility for the content of this publication.

ABBREVIATIONS

AI: Artificial Intelligence; MIS: Mean Item Score; SD: Standard Deviation; BIM: Building Information Modelling; FCT: Federal Capital Territory; NIQS: Nigerian Institute of Quantity Surveyors; QSRBN: Quantity Surveyors Registration Board of Nigeria; SPSS: Statistical Package for the Social Sciences; TAM: Technology Acceptance Model; DOI: Diffusion of Innovations; TOE: Technology-Organisation-Environment; KMO: Kaiser-Meyer-Olkin; CPD: Continuing Professional Development.

Conflict of Interest Statement

The authors declare that they have no known competing financial interests, personal relationships, or affiliations that could have influenced the work reported in this manuscript.

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